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Do auction formats matter in eBay auctions?

Ying-Tang Huang*, Jong-Rong Chen and Ying-Hui Chen

[1]Research Division V, Taiwan Insititute of Economic Research. 7F., No. 16-8, Dehui St., Jhongshan District, Taipei City 10461, Taiwan.
[2]Graduate Institute of Industrial Economics, National Central University, Taiwan 32001. Taiwan.
[3]Department of Economics, National Chengchi University, Taiwan 11605, Taiwan.

The proliferation of Internet auction elicits many interesting research questions for researchers engaging in this area. This study applies the empirical model to test whether the prices generated from different auction formats in eBay are equivalent. The daily observations in each format from eBay auctions are employed, and the empirical findings give rise to an important implication for internet auctions. The prices generated from different auction formats would be likely to converge except for the combination of the fixed-price listings with the best-offer option and the auction-style listings with the buy-it-now price. Therefore, the sellers' expected revenues would be equal even they specify their auctions with different formats.

Key words: Internet, price convergence, auction formats, eBay *JEL classifications*: D44.

INTRODUCTION

Online auction is very interesting and attractive because varieties of auction formats are offered and conducted sequentially or even in parallel. [1]The studies that investigate in the relationship between the auction formats and the seller's revenue (or transaction price) have appeared in large numbers in recent years (Bajari and Hortacsu (2004) and Ockenfels et al. (2006) and Hasker and Sickles (2010)). These studies are based on cross sectional analysis that could not provide a long-term view between these auction formats. Haruvy et al. (2008) and Haruvy and Popkowski Leszczyc (2009), however, mentioned that competition is ordinary in online auctions, and we believe that this scene may be mapped

by long-term relationship between auctions. [2]Therefore, this study would like to explore and examine the relationship by using eBay auctions.

In the previous studies about online auctions, buyout prices in online auctions may be the most interesting mechanism and attract many researchers to investigate. From Budish and Takeyama (2001), Mathews and Katzman (2006), to Reynolds and Wooders (2009), Shunda (2009), Inami (2011), Che (2011), Malmendier and Lee (2011), and Shahriar and Wooders (2011), they all try to explain the bidders' behavior when the sellers provide or not provide buyout price in online auctions. Otherwise, the ending rules in online auctions also draw much attention. Roth and Ockenfels (2002), Ariely et al. (2005), and Ockenfels and Roth (2006) are the pioneering in this topic, and then Tsuchihashi (2012) and Damiano et al. (2012) follow the pioneer and go a step further in this issue.

However, these previous studies lack dynamic view point may be arisen from two main reasons. First, their data cannot be transferred to time-series data, and it is

Corresponding author. E-mail: yingtang.huang@gmail.com , Tel: +886-933-255532.

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[1] For example, auctions with buy-it-now (or buyout price) may be one of the most well-known mechanisms in online auctions.Recently, eBay introduces a novel feature, the "Best Offer" option, to augment its fixed-price listing format in 2005. With Best Offer, sellers give buyers a chance to negotiate the price with them when sellers are selling an item with a fixed price.

[2]Haruvyet al. (2008) also examine auction data as a time series and not merely as endpoints is paramount in auction research with competing auctions.

difficult for them to apply any dynamic model. Otherwise, it may be difficult and almost impossible to process auctions by using two or more formats at the same time conventionally. However, the auctions in eBay take place when identical items are proceeding simultaneously.

In eBay auctions, either sellers or buyers could retrieve the results of completed auctions, either result in a sale or not, without any charge. [3]That is, it is possible for the agents to retrieve records of completed auctions when planning current transaction son the Internet auction sites defines a learning scheme that has been examined by Sonsino and Ivanova-Stenzel (2006). Therefore, the prices of the items in the same category may be correlated. Sonsino and Ivanova-Stenzel (2006)'s results suggest that the contents of samples retrieved from public databases may significantly affect the behavior of sampling agents. Since the price generation would be affected by the behavior(i.e., information retrieval) of the participants, the effects of records of completed auctions on the price generations in eBay should be expected. Other than the agents' behavior (both buyers and sellers) may be influenced by retrieving the information via the history records in eBay, there are still reasons for investigating in the relationship between auction formats using a time-series model. First, auctions on eBay are conducted sequentially or even in parallel (overlapped). Thus, the current highest prices and the current highest bids in eBay may be affected by the other auctions that are conducted at the same time. [4]Therefore, serial correlations between prices exist in eBay would be expected. Meanwhile, the other current prices from other auctions with similar (or even identical) items may affect the buyers' valuations for their items. Therefore, exploring the eBay auctions' results by using time series model should be reasonable.

In the light of the aforementioned concerns, the purpose of this paper is to empirically examine whether the transaction prices under different auction formats are likely to converge. A dynamic model proposed by Ravallion (1986) can visit in the issue of prices generation by using eBay as a target, and the new insight is also highlighted due to eBay auctions offering formats that differ from conventional auctions. Based on Ravallion (1986)'s model, the test results show that the transaction prices will not converge in the short run, but they are likely to converge in the long run in eBay auctions. The most related work to our study would be Li et al., (2006) which studied the final price prediction by collecting large amounts of historical exchange data from Each net in China. Their prediction was made by traditional statis-

tical methods to forecast the final prices of auction items, but they ignored the possible correlation between the current auctions and the past auctions' records.

The remainder of this article is organized as follows. Section 2 outlines the econometric model and hypotheses that are derived from Ravallion (1986). The empirical data and specifications are illustrated in Section 3. Section 4 describes and analyzes the empirical results. The concluding remarks and implications are provided in Section 5.

RAVALLION MODEL AND HYPOTHESES

Ravallion (1986) has proposed an empirical model to test spatial market integration. However, the 'markets' will be replaced by 'formats' in the following section while the purpose will be to test whether the prices from two different auction formats are equal. Hence, the static pattern of price formation among N formats can be represented as follows:

$$P_i = f_i(P_j, X_i), \ i, j = 1,...,N; i \neq j$$

whereX_i ($i = 1 ... N$) is a vector of other exogenous variables which might influence price formation in format i, and P_i and P_j are the prices of the ith and jth formats, respectively. The functions $f_i(i = 1,...,N)$ can be thought of as solutions to the appropriate conditions for the equilibrium of format i, taking into account the main spatial choices and the costs of adjustment facing traders when deciding where to sell. The econometric version of the above static pattern of price formation should embody a suitable dynamic structure; as is well known, dynamic effects can arise from a number of conditions in the underlying behavioral relations, including expectations formation and adjustment costs (Ravallion, 1986). In combining these considerations, the following econometric model of a T-period series of prices for 2 formats is specified as follows:

$$P_{it} = \sum_{h=1}^{m} a_{ih} P_{it-h} + \sum_{k=0}^{n} b_{jk} P_{jt-k} + X'_{it} c_i + e_{it}, \ t = 1, \ 2 \ ...T \qquad (1)$$

Where P_{it} and P_{jt} indicate the prices of the$i$th and $j$thformats at time t, respectively. P_{it-h} and P_{jt-k} respectively display the lagged terms of the$i$th and jth formats, while a_{ih} and b_{jk} are their corresponding coefficients. X'_{it} is the vector of other predetermined variables that could affect the price of the ith format, and c_i is its vector of coefficients. e_{it} is a white noise process or suitable error process.

In terms of the parameters of equation (1), for every two auction formats, one is the ith format and the other is the jth format. Ravallion (1986) proposed the following four testable hypotheses:

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[3] Other auction websites such as Yahoo! and Amazon do not provide the completed auction results in their sites. Luckily, eBay auction website is the largest auction site in the world (Bajari and Hortacsu, 2004; Ockenfelset al., 2006) and the empirical analysis based on eBay auctions would be representative.

[4]The difference between "the current highest price" and "the current highest bid"is depended on which bidding way is used by the buyer in eBay.One can refer to the following link: http://pages.ebay.com/help/buy/formats.html

H$_{01}$: Formats are segmented

Suppose the expected equilibrium price in the ith format is indicated by $E(P_{it})$, and that $E(P_{jt})$ illustrates the expected equilibrium price in the jth format. Then the following two equations can display the expectation for each format:

$$E(P_{it}) = E(P_{it-1}) = E(P_{it-2}) = ... = E(P_{it-h}) \qquad (2)$$

$$E(P_{jt}) = E(P_{jt-1}) = E(P_{jt-2}) = ... = E(P_{jt-h}). \qquad (3)$$

Equations (2) and (3) respectively indicate that the expected transaction prices for the ith or jth auction format in each period are equal. One can say that the auction formats are segmented if the following relationship holds:

$$E(P_{it}) \neq E(P_{jt}). \qquad (4)$$

By means of equations (2), (3), and (4), the first null hypothesis H$_{01}$ can be expressed as:

$$H_{01}: b_{jk} = 0, \ k = 0, 1...n. \qquad (5)$$

If H$_{01}$ is rejected, this implies that the price in the jth auction format may influence the price in the ith auction format. However, the price convergence is still not resolved before testing the other three hypotheses.

H$_{02}$: Strong form short-run price convergence

Ravallion (1986) demonstrates that strong form short-run price convergence is the effect of a price increase in the jth auction format that will be immediately passed on to the ith auction format price. That is, it implies that the prices in the two auction formats will instantaneously adjust to the same expected value as follows:

$$E(P_{it}) = E(P_{jt}), \ i \neq j. \qquad (6)$$

By contrast, when the price in the jth format is integrated with that in the ith format within one time period, the lagged effect of both the ith and jth formats cannot affect the future price in the ith auction format. Thus, the following two equations exhibit the relationships:

$$E(P_{it}) \neq E(P_{it-h}), \ h = 1, 2 ... m \qquad (7)$$

$$E(P_{it}) \neq E(P_{jt-k}), \ k = 1, 2 ... n \qquad (8)$$

Hence, by combining equations (6), (7), and (8), the null hypothesis may be presented as follows:

$$H_{02}: b_{j0} = 1, \text{ and } a_{ih} = b_{jk} = 0, \ h = 1...m, \text{ and } k = 0, 1...n.$$

If this null hypothesis is not rejected, then one can say that the price in the ith format will be integrated with the price in the jth format within one period. That is, the prices in the two different formats will instantaneously adjust to the same expected value.

H$_{03}$: Weak form short-run price convergence

The hypothesis of weak form short-run price convergence will also be tested. It allows the aggregate effects of both lagged prices (the ith and jth formats) on the future price of the ith format to only vanish on average when compared with the strong form short-run price convergence. Ravallion (1986) explains that the lagged variable may still have an impact on the future prices unless the lagged effects (both the ith and jth formats) aggregate to zero. Then, the null hypothesis can be expressed as follows:

$$H_{03}: b_{j0} = 1, \text{ and } \sum_{i=1}^{m} a_{ih} + \sum_{k=0}^{n} b_{jk} = 0.$$

If H$_{03}$ is not rejected, the aggregated effect of lagged prices (which combines the effects of the ith and jth formats) on the future price in the ith format may be zero and the short-run price convergence between the ith and jth formats will be achieved.

H$_{04}$: Long-run price convergence

A long-run equilibrium is one in which market prices are constant over time, undisturbed by any stochastic effects (Ravallion, 1986). Assume that equation (1) takes the form $P_{it} = P^* = P_{jt}$, and that $e_{it} = 0$ for all t; then equation (9) which follows demonstrates this expectation:

$$E(P_{it}) = ... = E(P_{it-h}) = P^* = E(P_{jt}) = ... = E(P_{jt-k}), \ h = 1...m, \text{ and } k = 1...n. \qquad (9)$$

By substituting the expectations into equation (1), we can then obtain the following equation (10):

$$P^* = \left(P^* \left(\sum_{k=0}^{n} b_{jk} \right) + X'_{it} c_i \right) \Big/ \left(1 - \sum_{h=1}^{m} a_{ih} \right) \qquad (10)$$

Moreover, when the prices in the ith and jth formats are convergent, the effect of other characteristics, X_{it}, on the prices of the ith format will vanish, That is, the coefficients of X_{it} will not be significant. Equation (10) can then be documented as follows:
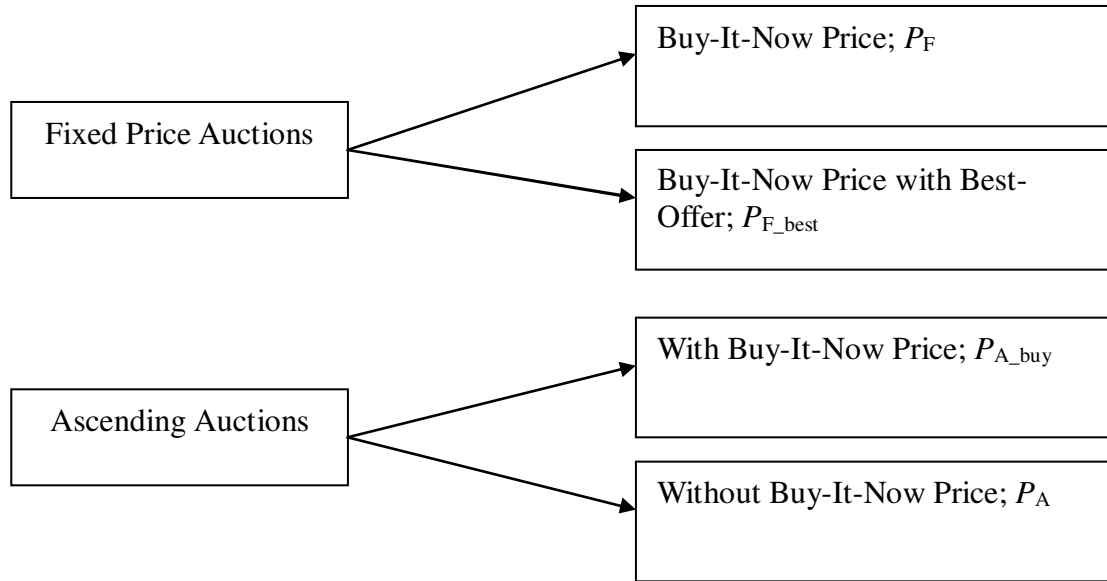
Figure 1. Auction formats on eBay.

$$1 - \sum_{h=1}^{m} a_{ih} = \sum_{k=0}^{n} b_{jk}$$

Therefore, the null hypothesis used to test the long-run price convergence can be illustrated by H_{04}:

$$H_{04}: \sum_{h=1}^{m} a_{ih} + \sum_{k=0}^{n} b_{jk} = 1. \qquad (11)$$

All the four null hypotheses proposed by Ravallion (1986) can be applied to test price convergence between the two auction formats. Hence, this study will estimate the price generating process suggested by equation (1) for each auction format and will then apply the above documentation to test the four hypotheses.

DATA SOURCE AND EMPIRICAL METHOD

Data collections and descriptions[5]

The empirical data were collected on eBay finished auctions, similar to that described in Li (2010) and Lucking-Reiley (1999).[6] To avoid the heterogeneous quality by different manufacturers (or brands), we collected the auction data for a single manufacturer (or brand). The authors followed Roth and Ockenfels (2002) and did not restrict the data to a particular subset of auctions. This is partly to avoid the danger that the data are dominated by a typical behavior patterns.

In the sample category, there are at least 1,500 auctions processed on eBay sites every day during our sample period, but the proportion of auctions that succeed is less than 30%.[7] Fortunately, four auction formats are simultaneously observed on eBay and collected by us. Thus, this paper can test whether the prices generations are getting equalized among the four formats. The pooled daily transaction prices for each auction format were applied in the empirical estimations.

The auction formats in eBay can be roughly classified into two types, which are fixed-price listings and auction-style listings (that is, ascending price auctions), and Figure 1 simply depicts their relationship. There is no ascending bidding process under fixed-price listings since the seller wants to sell the item only for a fixed-price. Recently (from 2005), eBay auction sites provide a new option for the sellers, namely, the best-offer, under fixed-price listings. That is, if the seller adopts the best-offer in his fixed-price listing, he/she gives buyers chances to negotiate the price with him/her. And then, the seller may reply to accept or reject the price offered by the buyer within the next 48 hours, or the offer price will expire. Therefore, P_F (the 1st format) represents the transaction prices series under fixed-price listings without the best offer in each period, and P_{F_best} (the 2nd format) denotes the transaction prices series when the best-offer is provided by the sellers under fixed-price listings.

The other two auction formats are both based on auction-style listings, and one of them provides a buy-it-now price. An auction-style listing needs to provide a minimum-bid (that is, starting-bid) for the buyer to start the ascending or competitive bidding process. However, if a seller provides a buy-it-now price in his auction-style listing, a buyer can avoid competition with other potential buyers by bidding the buy-it-now price to be the winner in the auction.[8] Hence, P_{A_buy} (the 3rd format) indicates the transaction prices when the buy-it-now price is available and also the transaction price in the

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[6] The reference link is: http://www.motors.ebay.com/

[7] The auction was not successful if no bid was placed, or the highest bid was not at least equal to the reserve price.
[8] When the auction receives no bid or the current bids are not at least equal to the secret reserve price, a bidder can bid the buy-it-now price on eBay auction sites.

2/08	2/19	3/02	3/13	3/24	4/04	4/16

——— P_F – – – – P_{A_buy}

- - - - - - P_{F_best} —– – –– P_A
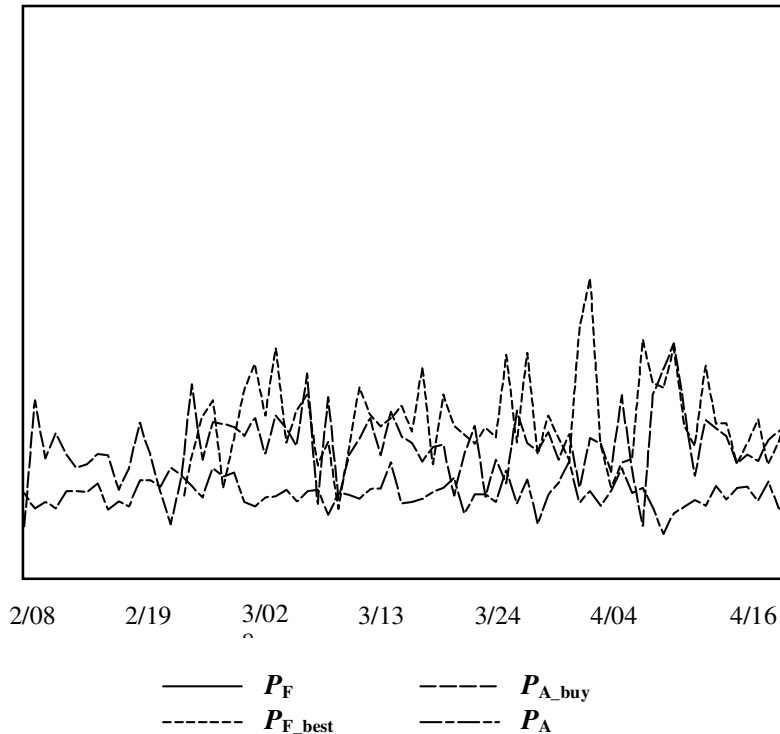
Figure 2. The time series plots of price of the four formats. Periods of above four figures are all from Feb. 8 to Apr. 21, 2008. The vertical axis implies the transaction prices, and the horizontal axis implies the days.

Table 1. Variable Descriptions.

	Mean	Std. Dev.	Max.	Min.	Skew.	Kurt.	Obs.
P_F:	15107.35	6876.261	42900	2750	.9735	5.3398	74
P_{F_best}:	13780.20	3926.448	26184	5950	.5276	3.2980	74
P_{A_buy}:	11532.89	3093.988	20490	4433	.0852	3.4927	74
P_A:	7292.864	1217.096	10159	3800	.1004	3.2825	74

Source: All statistics are estimated by this research.

auction-style listings. Otherwise, P_A (the 4th format) denotes the transaction prices of auction-style listings when it is ended by the second highest bid plus the minimum increment. The relationship between these four auction formats is depicted in Figure 1.

For the period from Feb. 8, 2008 to Apr. 21, 2008, data on 14,352 completed auctions on eBay auction sites were collected. There were 4,289 auctions that were successful, and each auction received at least one bid that was at least higher than the reserve price set by the seller. [9] Therefore, this paper divides these 4,289 observations into the four auction formats mentioned above. Finally, there are 74 daily observations from Feb. 8 to Apr. 21, 2008 for each auction format, for which can be conducted the empirical estimations and tests. Table 1 display the summary statistics, and Figure 2 shows the time-series plots of the four different types of auction. In Figure 2, though the transaction prices series of fixed-

price listings, that is, P_F seems more volatile than the other three price series, the four prices series may co-integrate by eyeball test. In what follows, we will describe the empirical steps and methodology.

The Estimations of the Ravallion Model

Augmented Dickey-Fuller tests

We seek to make sure that the stationarity of each series is a necessary condition for estimating an empirical model with time series data, or else the non-stationary series may lead to spurious regressions (Enders, 2004). To avoid the possibility of a spurious relationship, the well-known ADF (augmented Dickey-Fuller, henceforth ADF) test Dickey and Fuller (1979, 1981) can be used to certify the stationarity of the series.

The ADF test statistics for the four series are shown in Table 2. We can observe that all sequences in the sample set are stationary, and can conclude that the estimation of the model can avoid the possibility of spurious regression.

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[9] On eBay, the reserve price can be meant to be the 'starting bid (minimum bid)' or 'secret reserve price'. Among these 4,289 auctions, there are 107 auctions based on the 1st format, 468 on the 2nd format, 695 on the 3rd format, and 3,019 on the 4th format.

Table 2. Augmented Dickey-Fuller (ADF) Tests.

	γ (p-value)	ADF-statistic	Q3 (p-value)	Q6 (p-value)	Q9 (p-value)
P_F:	-.833 (.0)	-7.143	3.004 (.391)	5.643 (.464)	7.820 (.552)
P_{F_best}:	-.913 (.0)	-7.741	2.898 (.408)	4.991 (.545)	6.747 (.663)
P_{A_buy}:	-.995 (.0)	-8.683	.529 (.912)	2.676 (.848)	3.954 (.914)
P_A:	-.853 (.0)	-7.187	3.391 (.335)	5.283 (.508)	7.324 (.603)

Source: *All statistics are estimated by this research. **The testing model:
$\Delta P_t = c_0 + c_1 t + \gamma P_{t-1} + \sum_{i=1}^{n} \alpha_i \Delta P_{t-i} + \varepsilon_t, t = 1, 2 \dots T$. Q3, Q6, and Q9 are diagnostic tests of
data generation process, and their results may guarantee the error term (e_{it}) at each
model is white noise. ***The critical values of 1%, 5%, and 10% are -3.521, -2.901, and -2.588 respectively.

Empirical model estimations

In order to develop a more precise data generating process, equation (1), the econometric package in E-Views, is applied. For convenience, we limit the largest lagged price series in the estimation for both the ith and jth formats to 7. On the other hand, too many lag terms in the estimations may lack degrees of freedom and lead to inefficient estimations. All the possible lag-combinations of each of the two formats are included in the estimations and the results of the estimations are shown in Table 3. Moreover, the error term when estimating equation (1) is required to be a white-noise process, in which the error term sequence has a mean of zero, a constant variance, and is serially uncorrelated. That is, well-known diagnostic tests are performed following the estimations. Hence, the following two conditions are necessary in searching for a suitable data generation process (Enders, 2004):

$E(e_{it}) = E(e_{it-1}) = E(e_{it-2}) = \dots = 0, E(e^2_{it}) = E(e^2_{it-1}) = E(e^2_{it-2}) = \dots = \sigma^2$.

To ensure the estimated coefficients are unbiased, the test statistics for Q3, Q6, and Q9 in Table 4 are used to perform the diagnostic tests. These three statistics reject the serial correlation in the error term, which is generated when estimating equation (1).Hence, the estimated coefficients of equation (1) are unbiased due to its error term being white noise. After ensuring that the estimations are unbiased, the parsimonious model is confirmed by SBIC (Schwarz Bayesian Information Criterion), that the estimation with the smallest SBIC was applied in the following analysis.

Finally, these estimated coefficients of the models are used to test the four hypotheses that are discussed in Section 2. Based on the Wald-test, the test statistics for the four hypotheses, H_{01}, H_{02}, H_{03}, and H_{04}, are displayed in the right four columns of Table 4, and are further summarized in Table 4. In the next section we discuss the test results.

RESULTS AND DISCUSSION

The test results are summarized in Table 4, where "Rejected" indicates that the null hypothesis is rejected and "Not rejected" signifies that the opposite conclusion has been reached.

One can find that both hypotheses of H_{02} and H_{03} are rejected. This would imply that the prices of different auction formats cannot immediately adjust to the same expected value in one day, even though the price information may be transmitted quickly through internet

auction sites. [10] We then go a step further to examine the results of testing H_{01} (formats are segmented) and H_{04} (long-run convergence).

Notice that the results of testing H_{01} and H_{04} can be compared at the same time. That is, if H_{01} is rejected, then H_{04} will not be expected to be rejected. Or, in other words, when the two transaction price sequences exhibit a relationship over the long run (that is, fail to reject H_{04}), H_{01} should be rejected to indicate that the two formats are not segmented. From Table 4, almost all the tests report that the H_{01}s are rejected and the H_{04}s are not rejected, except for the estimation of the regressions for the fixed price auctions with the best offer being P_{it} and the ascending auctions with the buy-it-now price being P_{jt}.[11] Hence, we note that none of the test results is paradoxical, and in what follows we give some explanations for these results.

To our knowledge, both theoretical and empirical studies conclude that different auction formats may give rise to different levels of revenue among sellers, especially auction-style listing with a buy-it-now or buyout price (Ockenfels et al., 2006). However, eBay auctions are simultaneously and sequentially proceeding. Otherwise under open auctions,[12] buyers can monitor whether the prices is higher than the other auctions in real time, and then decide if they should participate in the auction, revise their bids or drop out of the auction (e.g., by not raising their bids above the prevailing market-clearing bids) (Koh et al., 2007). This might be the reason why the transaction prices for different auction formats will eventually converge to the same expected value.[13]

Furthermore, eBay sites provide the information that

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[10] Since this study empirically uses daily observations, 'one period' can also be referred to as 'one day'.

[11] However, the test results for the regression of P_{F_best} (i.e., P_{it}) on P_{A_buy} (i.e., P_{jt}) are still not paradoxical.

[12] The quota on vehicle licenses in Singapore is an example of an open auction. Clearly, eBay sites also provide similar types of open auctions.

[13] Recently, Malmendier and Lee (2011) compare online auction prices to fixed prices for the same item on the same webpage. They found that 42 percent of auctions exceed the simultaneous fixed price.Interestingly, their concluding remarks are far different from ours.

Table 3. Ravallion Model Estimations and Tests (p-values are in the parentheses).

P_{it}	P_{jt}	Ravallion Model	R-squared	adj. R-squared	Q3	Q6	Q9	SBIC	H01	H02	H03	H04
P_F	P_{F_best}	$P_{it}=10750.74+.202P_{it-5}-.268P_{jt}+.397 P_{jt-3}$ (.033) (.085) (.196) (.056)	.137	.100	2.514 (.473)	3.155 (.789)	3.219 (.955)	20.577	3.522 (.035)	18.26 (.0)	27.38 (.0)	3.694 (.059)
	P_{A_buy}	$P_{it}=8302.18-.197P_{it-3}+.318P_{jt}+.571P_{jt-4}$ (.070) (.099) (.232) (.028)	.115	.075	1.540 (.673)	2.380 (.882)	4.509 (.875)	20.609	3.310 (.043)	4.299 (.008)	4.406 (.016)	.683 (.412)
	P_A	$P_{it}=9066.51+.0116P_{it-5}-.888P_{jt}+1.543P_{jt-4}$ (.210) (.334) (.175) (.021)	.146	.106	2.366 (.500)	2.810 (.832)	4.831 (.849)	20.567	3.902 (.025)	6.457 (.001)	8.294 (.001)	.058 (.810)
P_{F_best}	P_{A_buy}	$P_{it}=14254.26-.235P_{it-3}+.241P_{jt}$ (.0) (.046) (.121)	.080	.053	.805 (.848)	4.563 (.601)	8.630 (.472)	19.470	2.472 (.121)	15.765 (.0)	15.765 (.0)	30.297 (.0)
	P_A	$P_{it}=11759.36-.131P_{it-3}-.404P_{jt}+.923P_{jt-7}$ (.007) (.275) (.276) (.018)	.133	.092	.254 (.968)	6.287 (.392)	12.51 (.186)	19.476	3.350 (.041)	7.508 (.0002)	8.442 (.001)	1.324 (.254)
P_{A_buy}	P_A	$P_{it}=10752.54+.035 P_{it-2}-.521P_{jt}+.580 P_{jt-4}$ (.004) (.767) (.075) (.049)	.109	.069	.289 (.962)	2.629 (.854)	5.173 (.819)	18.977	4.005 (.023)	11.501 (.0)	17.190 (.0)	3.967 (.051)

Source: All statistics are estimated by this research. Ravallion model: $P_{it} = \sum_{h=1}^{m} a_{ih} P_{it-h} + \sum_{k=0}^{n} b_{jk} P_{jt-k} + e_{it}$, $t = 1, 2 \dots T$. **Each model is selected by SBIC (Schwarz Bayesian information criterion). Q3, Q6, and Q9 are diagnostic tests of data generation process, and their results may guarantee that the error term (e_{it}) at each Ravallion estimation is white noise. *** H01: prices are uncorrelated under different mechanism; H02: strong form short-run price convergence; H03: weak form short-run price convergence; H04: long-run price convergence.

Table 4. Summary of Ravallion Model Tests.

P_{it}	P_{jt}	Hypothesis			
		H01: Formats are segmented	H02: Strong form short-run price convergence	H03: Weak form short-run price convergence	H04: Long-run price convergence
P_F	P_{F_best}	Rejected[c]	Rejected[c]	Rejected[c]	Not rejected[a]
	P_{A_buy}	Rejected[c]	Rejected[c]	Rejected[c]	Not rejected[b]
	P_A	Rejected[c]	Rejected[c]	Rejected[c]	Not rejected[b]
P_{F_best}	P_{A_buy}	Not rejected[b]	Rejected[c]	Rejected[c]	Rejected[c]
	P_A	Rejected[c]	Rejected[c]	Rejected[c]	Not rejected[b]
P_{A_buy}	P_A	Rejected[c]	Rejected[c]	Rejected[c]	Not rejected[a]

Source: All statistics are estimated by this research. *The superscript 'a', and 'b' denote the statistic is fail to be rejected at 5% and 10% significant level respectively. **The superscript 'c' denotes the statistic is to be rejected at 5% significant level.

enables the registered users to trace back the statuses of the auctions that have been completed during the past 14 days, that is information retrievals. [14]Either buyers or sellers in eBay auctions could refer to the records of the completed auctions if necessary, and this could also induce more informational transparency in eBay auction sites. The winning bidder may retrieve the information of completed auctions, and then bid accordingly. Therefore, the prices between formats are insignificantly different from each other.

Otherwise based on our data, the proportion of auctions that were successful was less than thirty percent (29.88%), so that more than 70% were unsuccessful. Therefore, the proportion of unsuccessful auctions might be significantly higher than the proportion of successful ones. The authors have therefore carefully checked the whole data set and have found that the reserve prices

(that is, the seller's minimum willingness to accept) of the unsuccessful auctions are significantly higher than the transaction prices of the successful auctions. Hence, consumers in eBay auction markets might have greater power to determine the transaction price, regardless of which format a seller would like to offer.

Most test results (more than 83%) show that the transaction prices would converge. Hencein eBay, the transaction prices might be expected to converge even though the sellers may wish to make more revenue by offering different formats, and the revenue equivalence theorem is found to hold in eBay auctions.

Conclusion

The study attempts to investigate whether the auction formats matter by the prices in eBay auctions. Unlike the previous studies that consider the prices generations

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[14]Yahoo auction sites do not provide this specific service for users of their site.

between formats by static that may bias the conclusion due to such as information retrieval by the participants in eBay (Sonsino and Ivanova-Stenzel, 2006).This study goes a step further to estimate the prices generation process by a dynamic model by using transaction prices for different formats in eBay. The 74 daily observations from February 8 to August 21 in 2008 on eBay auction sites are examined to test whether the transaction prices between different formats are equivalent.

The test results show that the transaction prices (also the seller's revenue) for different auction formats cannot immediately adjust to the same expected value, that is, the tests for short-run convergence are rejected. Furthermore, except for P_{F_best} which is P_{it} and P_{A_buy} which is P_{jt} in Ravallion (1986)'s estimation, the other results from testing H_{01} show that neither of the two formats is segmented, and the hypotheses of long-run price convergence ($H_{04}s$) are not rejected.

Hence, we expect that the prices would converge even though the seller might expect higher revenue by offering a specific format (for example, auctions with a buy-it-now price). Therefore, our empirical results may provide new insights for online auctions. That is, the price series will be converged even under different auction formats.

In addition, common value element may be existed in eBay auctions which are with repeated and simultaneous objects. Under these phenomenon, the prices could converge to the same value, and then the bidders may decide whether they should participate in the auction, and revise their bids or drop out of the auction (e.g., by not raising their bids above the prevailing market-clearing bids) (Koh et al., 2007).

There is still one test result (P_{F_best} on P_{A_buy}), however, that leads to the rejection of the prices will converge to the same value. The short time length of the data set may be the reason for this, and may be an issue that should become the focus of future research. In addition, the empirical results can enable us to more precisely estimate whether the empirical data can be examined further to avoid the possible effects of heterogeneity. In other words, this paper, among others, has to provide new insights into testing the prices generation process in the context of online auctions. However, when more convincing data become available, we can re-estimate the related empirical model and obtain more promising results.

As an exploratory study, the regression results of this study imply the prices will be equivalent. In the future, we wish to shed more light on possible strategies used by buyers and sellers if more regression results are obtained in the future study are reliable, or on more detailed characteristics of the different auction formats that might lead them to generate different prices. Other wise, using a time series econometric model does not involve considering the endogenous choice of auction formats that result from the seller choosing which auction format to adopt (Hansen, 1986). This is indeed an important

limitation of the econometric model estimations in this study, and we therefore hope that this shortcoming can also be resolved in the future.

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